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Adaptive Search Through Constraint Violations

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Restructuring consists of a change in the representation of the current search state, a process which breaks an impasse during problem solving by opening up new search paths. A corpus of 52 think-aloud protocols from the domain of geometry was scanned for evidence of restructuring. The data suggest that restructuring is accomplished by re-parsing the geometric diagram.

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Knowledge and Understanding in Human Learning

Knowledge and Understanding in Human Learning (KUL) is an umbrella term for a loosely connected set of activities lead by Stellan Ohlsson at the Learning Research and Development Center, University of Pittsburgh. The aim of KUL is to clarify the role of *world knowledge* in human thinking, reasoning, and problem solving. World knowledge consists of general principles, and contrasts with facts (episodic knowledge) and with cognitive skills (procedural knowledge). The long-term goal is to answer six questions: How can the conceptual content of a particular knowledge domain be identified? How can a particular person's knowledge of a given domain be diagnosed? How is principled knowledge utilized in insightful performance? How does principled knowledge influence procedure acquisition? How is principled knowledge acquired? How can instruction facilitate the acquisition of principled (as opposed to episodic or procedural) knowledge? Different methodologies are used to investigate these questions: Psychological experiments, computer simulations, historical studies, semantic, logical, and mathematical analyses, instructional intervention studies, etc. A list of KUL reports appear at the back of this report.

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Abstract

We describe HS, a production system that learns control knowledge through adaptive search. Unlike most other psychological models of skill acquisition, HS is a model of analytical, or knowledge-based, learning. HS encodes general domain knowledge in *state constraints*, patterns that describe those search states that are consistent with the principles of the problem domain. When HS encounters a search state that violates a state constraint, it revises the production rule that generated that state. The appropriate revisions are computed by regressing the constraint through the action of the production rule. HS can learn to solve problems that it cannot solve without learning. We present a Blocks World example of a rule revision, empirical results from both initial learning experiments and transfer experiments in the domain of counting, and an informal analysis of the conditions under which this learning technique is likely to be useful.

Introduction

The acquisition of control knowledge is a central problem in machine learning research. In one formulation of the control knowledge problem, a weak but general problem solver searches for the solution to a problem with an initial set of incomplete or faulty problem solving rules. Learning mechanisms such as discrimination (Langley, 1985), subgoaling (Ohlsson, 1987a), or version spaces (Mitchell, 1982) can be applied to the information in the search tree to identify conditions that will enable the rules to solve the problem, or the relevant class of problems, with less search. Psychologists are interested in this learning scenario because it offers a possible model of how humans learn cognitive skills through practice (see, e. g., Anderson, 1989; Holland, Holyoak, Nisbett, & Thagard, 1986; Laird, Rosenbloom, & Newell, 1986; VanLehn, in press).

Psychological models of skill acquisition employ different problem solving mechanisms (forward search, backward chaining, means-ends analysis, planning, universal weak method) and different learning mechanisms (analogy, chunking, composition, discrimination, grammar induction, subgoaling), but with only a few exceptions (Anderson, 1989; Ohlsson, 1987b; Ohlsson & Rees, 1988) they have focussed on *empirical* learning methods. They identify rule conditions by performing some form of induction (in a broad sense) on the examples of correct and incorrect operator applications embedded in the search tree. Empirical learning methods contrast with *analytical* methods such as explanation-based learning (EBL) which identify rule conditions by applying knowledge about the relevant problem domain (Minton, 1988). But analytical learning methods are particularly interesting from a psychological point of view, because they offer a possible explanation of the facilitating effect of domain knowledge on procedure acquisition. Psychological experiments have shown that knowledge of the principles of a domain enables people to learn procedures faster and apply them more flexibly (see, e. g., Kieras & Bovair, 1984) as compared to conditions in which such knowledge is absent.

We describe a technique for knowledge-based procedure acquisition which is based on the idea that the main function of knowledge is to constrain the possible states of affairs. Incomplete control knowledge will frequently lead to the generation of search states that violate such constraints. The information contained in constraint violations can be used to identify new rule conditions adaptively, before a correct solution path has been found (Mostow & Bhatnager, 1986). The technique is implemented in a running simulation model called HS. We present data from both initial learning experiments and transfer experiments, and an informal analysis of the conditions under which our learning technique is likely to be useful. Our system is related to the FAILSAFE system described by Mostow and Bhatnager (1986), to the proceduralization hypothesis proposed by Anderson (1989), and to the planning net model of counting competence put forward by Smith, Greeno, and Vitolo (in press). A comparison with these systems will be postponed until the discussion section.

Knowledge as Constraints on Possible Situations

We are interested in the cognitive function of general knowledge. Many discussions of knowledge implicitly assume that the function of general knowledge is either to summarize particular facts or to enable explanations and predictions. There is no doubt that knowledge has those functions. However, we want to suggest that knowledge *also* can have the function of constraining the set of situations that one can reasonably expect to happen. The laws of conservation of mass and energy and the laws of commutativity and associativity of addition are examples of general principles that constrain the possible states of affairs. Faulty control knowledge, e. g., an incorrect laboratory procedure or a buggy addition algorithm, is likely to lead to violations of such constraints.

To capture the idea of general knowledge as constraints on possible situations, we encode a principle C as a *state constraint*, i. e., as an ordered pair of patterns $<C_r, C_s>$ in which C_r is the *relevance pattern* and C_s is the *satisfaction pattern*. For example, the law of commutativity of addition expressed as a state constraint becomes *if* $x + y = p$ *and* $y + x = q$, *then it should to be the case that* $p = q$. The principle of one-to-one mapping becomes *if object A has been assigned to object B, then there should not be some other object X which also has been assigned to B.* The law of conservation of mass becomes *if* M_1 *is the mass of the ingredients in a chemical experiment, and* M_2 *is the mass of the products, then it should to be the case that* $M_1 = M_2$. A constraint consists of a pair of patterns because all constraints are not relevant for all problem types. The relevance pattern of a state constraint specifies those search states (situations) in which the corresponding principle applies. The purpose of expressing domain knowledge in state constraints is to enable the HS system to efficiently identify search states that violate principles of the domain. This requires a MATCH(C, S) predicate that can decide whether a given pattern matches a given search state. We have used a RETE pattern matcher (Forgy, 1982) as our MATCH predicate.

HS is a relatively standard production system architecture that has been augmented with the state constraint representation. The system is given a problem space (an initial state, a set of operators, and a goal criterion), and a set of (minimally constrained) production rules. The initial state is a fully instantiated description of the problem, an operator consists of an addition list and a deletion list, and the goal criterion is a pattern. The system solves problems by forward breadth-first search through the problem space. Forward search is a very weak method, but since HS searches adaptively (Mostow & Bhatnager, 1987), improving its rules before it has found a complete solution path, it need not search the problem space exhaustively. HS searches until it encounters a constraint violation, learns from that violation, backs up to the initial state, and tries anew to solve the problem. If a state violates more than one constraint, HS selects one at random to learn from.

The identification of constraint violations proceeds as follows. When a production rule P: R --> O with condition R and action O is applied to a search state S_1, thereby generating a descendent state S_2, the relevance patterns of all constraints are matched against the new state S_2. If the relevance pattern C_r of constraint C does not match S_2, then C is irrelevant for that state and no further action is taken with respect to that constraint; if C_r does match, then C is relevant and the satisfaction pattern C_s is also

matched against S_2. If C_s matches, no further action is taken. But if C_s does not match, then a constraint violation is recorded. State constraints do not generate conclusions or fire operators; nothing is added to the problem description when a state constraint is applied. A state constraint functions as a classification device that sorts search states into those that are consistent with the principles of the domain and those that are not.

Learning from Constraint Violations

There are two types of constraint violations in the HS system. Suppose that production rule P: R --> O was evoked in state S_1, leading to the generation of a new state S_2. In a *Type A* violation the constraint C is irrelevant in S_1, and it is relevant but not satisfied in S_2. In a *Type B* violation the constraint C is both relevant and satisfied in S_1, and it is relevant but not satisfied in S_2. Each type violation requires two different revisions of the rule P. The new rules are computed by regressing the constraint through the operator, but we will explain the technique with a set-theoretic notation which shows clearly why each type of violation gives rise to *two* new rules.

Rule revisions for Type A violations. If the relevance pattern C_r does not match state S_1, but does match its immediate descendent S_2, then the effect of operator O is to create expressions that enable C_r to match. But since, *ex hypothesi*, the constraint C is violated in S_2, O does not create the expressions needed to complete the match for the satisfaction pattern C_s. This situation warrants two different revisions of the rule P that fired O. First, the condition of P should be revised so that the revised rule--call it P'--only matches in situations in which O does not complete the relevance pattern for C, thus ensuring that the constraint remains irrelevant. Second, the condition of P should be revised so that the revised rule--call it P"--only fires in those situations in which *both* the relevance *and* the satisfaction patterns of C are completed, thus ensuring that the constraint becomes satisfied.

Revision 1. Ensuring that the constraint remains irrelevant. O will complete C_r when the parts of C_r that are not added by O are already present in S_1. Those parts are given by $(C_r - O_a)$, where the symbol "-" signifies set difference. To limit the application of rule P to situations in which operator O will not complete C_r, we augment the condition of P with the negated expression *not* $(C_r - O_a)$. The new rule is

$$P'\text{: } R \;\&\; \textit{not}\,(C_r - O_a) \dashrightarrow O$$

where "&" signifies conjunction.

Revision 2. Ensuring that the constraint becomes satisfied. To guarantee that C_r will become complete, we augment the condition R with $(C_r - O_a)$. To guarantee that C_s will also become complete we augment R with those parts of C_s that are not added by O. They are given by $(C_s - O_a)$, so the desired effect is achieved by adding the entire expression $(C_r - O_a)$ u $(C_s - O_a)$ to R, where the symbol "u" signifies set union. The new rule is

$$P'': R \cup (C_r - O_a) \cup (C_s - O_a) \rightarrow O$$

Rule revisions for Type B violations. If the constraint C is both relevant and satisfied in state S_1, and relevant but not satisfied in S_2, the effect of operator O is to destroy the match for the satisfaction pattern C_s, but not for the relevance pattern C_r. This situation also warrants two revisions of rule P.

Revision 1. Ensuring that the constraint is irrelevant. Rule P is revised so that it will only fire in situations in which constraint C is not relevant and in which C will not become relevant. This is accomplished by adding the negation of the relevance pattern C_r to the condition R of the rule. The new rule is

$$P': R \ \& \ \textit{not}\ C_r \rightarrow O$$

Revision 2. Ensuring that the constraint remains satisfied. Rule P is replaced by a rule P" which only fires in situations in which the constraint remains satisfied. This is done in two steps. The first step is to constrain the rule to fire only in situations in which the constraint is relevant. This is accomplished by adding the relevance pattern C_r to the rule condition. The second step is to constrain the rule to situations in which the match of the satisfaction pattern is unaffected by the action of operator O. This is accomplished by adding the negation of the intersection between the satisfaction pattern and the deletion list, *not*($C_s \cap O_d$), to the rule condition. The desired effect is attained by adding the entire expression $C_r \cup$ *not*($C_s \cap O_d$), so the new rule is

$$P'': R \cup C_r \cup \textit{not}(C_s \cap O_d) \rightarrow O.$$

The above description of the learning algorithm is simplified in the following respects: (a) Rules are not replaced by their descendents. The old rules are retained, but their descendents are preferred during conflict resolution. (b) In order to add parts of a constraint to a rule condition correspondances must be computed between the variables in the constraint and the variables in the rule. In the implementation those correspondances are computed by the regression algorithm. (c) A negated condition can cease to match as the result of the addition of expressions to a search state. Our revision algorithm handles those cases as well. (d) There are cases in which one of the two revisions results in the empty list of new conditions. In those cases only one new rule is created.

Revising a Blocks World Rule

The HS system has mainly been applied to arithmetic tasks such as counting a collection of objects, and subtracting multi-digit integers (Ohlsson & Rees, 1988). We nevertheless illustrate the rule revision algorithm with an example from the Blocks World, because of the widespread familiarity with this domain. Successful performance in the Blocks World requires knowledge of where blocks can be put down. Putting a block on the table or on top of a stack generally results in a stable situation, but trying to put a block on another block that already has other blocks stacked on top of it is likely to lead to the collapse of the stack. The following Blocks World rule says that *if the hand is holding a block, and the goal is to put*

the block down, and the hand is in the up position, and there is a possible support, then lower the hand:

(GOAL PUTDOWN <Block>)(ISA BLOCK <Block>)(HOLDING HAND <Block>)
(POSITION HAND UP)(ISA SUPPORT <Support>)
-->
LowerHand(<Block>, <Support>)

The operator LowerHand lowers the block onto the support, but does not let go of the block. It is defined by the deletion list

O_d = {(POSITION HAND UP)}

and the addition list

O_a = {(POSITION HAND DOWN)(ON <Block> <Support>)}.

Since blocks are members of the category *supports*, this rule will attempt to lower the block onto any other block in the world. If the supporting block is in the middle of a stack, this operation violates the principle that *only one block can be on top of another block*, which can be expressed as a state constraint with relevance pattern

C_r = {(ON <Block> <Support>)(ISA BLOCK <Support>)}

and satisfaction pattern

C_s={(*not* (ON <OtherBlock> <Support>) (*not* (EQUAL <OtherBlock> <Block>))))}

Lowering a block until it rests on a block that is not a top block, i. e., a block which has other blocks resting on it, leads to a violation of this constraint. Since the constraint cannot be relevant before the hand is lowered, this is a Type A violation.

Revision 1. Ensuring that the constraint remains irrelevant. The difference between the relevance pattern C_r and the addition list O_a is

C_r - O_a = {(ISA BLOCK <Block>)}.

The negation of this expression is added to the rule condition, so the new rule becomes:

(Goal: PUTDOWN <Block>)(ISA BLOCK <Block>)(HOLDING HAND <Block>)
(POSITION HAND UP)(ISA SUPPORT <Support>)
(not (ISA BLOCK <Support>))
-->
LowerHand(<Block>)

where the new condition is in boldfaced typefont. This rule says that it is possible to put a block down on any support that is not a block. In the standard version of the Blocks World, the only support that is not a block is the table.

Revision 2. Ensuring that the constraint becomes satisfied. As noted above the difference (C_r - O_a) is in this case

C_r - O_a = {(ISA BLOCK <Support>)}.

Subtracting the addition list O_a from the satisfaction pattern C_s returns the satisfaction pattern itself,

because they do not have any expressions in common in this case. Adding $\{(C_r - O_a) \cup (C_s - O_a)\}$ to the rule therefore generates the new rule

(Goal: PUTDOWN <Block>)(ISA BLOCK <Block>)(HOLDING HAND <Blocks>)
(POSITION HAND UP)(ISA SUPPORT <Support>)
(ISA BLOCK <Support>)
(not [(ON <OtherBlock> <Support>)(not (EQUAL <OtherBlock> <Block>))]

-->
LowerHand(<Block>, <Support>)

where the new conditions are in boldfaced typefont. This rule says a block can be lowered onto another block, if that other block is a top block, i. e., if it does not have any blocks resting on it.

In summary, the revision algorithm takes as input a violation of the constraint *only one block can be on top of another block* and sorts out the two action possibilities that are consistent with it--either put a block down on the table, or put it down on a top block--encoding each possibility in a separate production rule. The two new rules are not perfect, of course, and they will be revised further when they violate other constraints. Repeated revision of rules is a central feature of learning in the HS system.

Evaluation

The task of quantifying a collection of objects by counting them is interesting from the point of view of the cognitive function of principled knowledge, because observations of children show that they understand the principles that underly counting (Gelman & Gallistel, 1978; Gelman & Meck, 1986). Modifying slightly the analysis by Gelman and Gallistel (1978), we identify three counting principles: (a) *The Regular Traversal Principle* which says that correct counting begins with unity and generates the natural numbers in numerical order. (b) *The One-One Mapping Principle* which says that each object should be assigned exactly one number during counting. (c) *The Cardinality Principle* which says that the last number to be assigned to an object during counting represents the numerosity of the counted collection. These three principles form the conceptual basis of the procedure for *standard counting,* in which the objects are counted in any order. In order to probe children's understanding of counting, Gelman and Gallistel (1978) invented two non-standard counting tasks, *ordered counting,* in which the objects are counted in some pre-defined order (e.g., from left to right), and *constrained counting,* in which the objects are counted in such a way that a designated object is assigned a designated number. These three counting tasks require different procedures (control knowledge), but all three procedures are based on the above principles.

HS can learn the correct procedure for either of the three counting tasks. The input to the system consists of a problem space for counting, state constraint representations of the counting principles, and an initial rule set. Our representation for the counting task is very fine-grained, and the operations of setting and retracting goals are treated as search steps, so counting three objects requires 48 steps through the problem space. Since the initial rules are minimal, the branching factor before learning is between two and four, giving a search space of more than $60 {}^{*} 10^9$ states. This search problem is too large

Table 1: Initial Learning Effort for Three Counting Tasks.

	Effort measure		
Counting task	Rule revisions	Production system cycles	Search states
Standard	12	854	979
Ordered	11	262	294
Constrained	12	451	507

to be solved by brute force, but since HS searches adaptively, the system is nevertheless successful. Table 1 show three measures of the amount of work required to learn each counting procedure. The number of rule revisions required is approximately the same (either 11 or 12) for each procedure. The number of states visited during learning is less than 10^3, so the system only needs to visit a very small portion of the total search space in order to find those rule revisions. In terms of either the number of production system cycles or the number of search states visited, standard counting is harder to learn than constraint counting, which in turn is harder to learn than ordered counting, a prediction which in principle is empirically testable.

Observations of children show that they can easily switch from standard counting to either of the two non-standard counting tasks (Gelman & Gallistel, 1978; Gelman & Meck, 1986). The most plausible explanation for this flexibility is that children can derive the control knowledge for the non-standard counting tasks from their knowledge of the counting principles. To simulate this flexibility we performed transfer experiments with HS. Once the system had learned a correct counting procedure, we gave it counting problems of a different type than the type on which it had practiced. For example, having practiced on standard counting, the system might be given constrained counting problems, and vice versa. To solve these problems the system had to adapt the already learned control knowledge to the new task. Since there are three different counting tasks, there are six possible transfers, all of which HS carried out successfully. Table 2 shows three measures of the amount of work required for each of the six transfers.

Three conclusions emerge from Table 2. First, the number of rule revisions is between one order of magnitude lower than the number of production system cycles or the number of search states visited, so HS predicts that the density of learning events during practice is low. Second, there is substantial transfer between the three counting tasks. The number of rule revisions required to learn any one of the three counting tasks from scratch is either 11 or 12; the number of revisions required to transfer to a different task is between 0 and 3 in five cases, a saving of approximately 75 %. Third, transfer is asymmetric. Ordered counting does not transfer to constrained counting, but constrained counting transfers very well

Table 2: Learning Effort for Six Transfer Tasks in the Counting Domain.

Training task	Transfer task: Standard counting	Ordered counting	Constrained counting
Standard			
Revisions	-	2	2
Cycles	-	110	127
States	-	119	141
Ordered			
Revisions	1	-	11
Cycles	184	-	297
States	209	-	334
Constrained			
Revisions	0	3	-
Cycles	162	154	-
States	180	190	-

to ordered counting. Although we do not yet possess the relevant observations, these predictions are in principle empirically testable.

Discussion and Related Work

In which task domains is constraint violation likely to be a effective? The technique allows a system to identify, out of all possible paths in a search space, those paths which are consistent with the principles of the task domain. Let us call those *correct* paths. A correct path is not necessarily a *useful* path, i. e., a path that leads to a desired problem solution. Constraint violation is likely to be effective when (a) the ratio of correct to possible paths is small, i. e., when correct paths are rare, and (b) the ratio of useful to correct paths is high, i. e, when many correct paths are useful. In the counting domain *every* step is regulated by the counting principles, so every correct path is also a useful path. Another domain in which constraint violation might be useful is predicting the outcomes of chemical experiments, where all reaction paths that are consistent with the laws of chemistry need to be considered. But in proof spaces in algebra and geometry, where there are many mathematically correct paths which do not lead to a desired theorem, constraint violation is likely to be ineffective.

Our system is similar in basic conception to the FAILSAFE system described by Mostow and Bhatnager (1987) that operates in a floor planning domain. Both systems learn control knowledge during forward

search by using the information in failed solution paths to revise the rules that lead to those paths. Both systems encode domain knowledge as constraints on correct solutions, and both systems use regression to identify the new rule conditions. However, there are also differences. First, Mostow and Bhatnager (1987) argue that one of the advantages of adaptive search is that it becomes possible to make progress on problems for which the completion of a correct solution path through unconstrained search is infeasable. However, this advantage does not seem to be realized in the FAILSAFE system, since the system in fact completes an entire floorplan before testing whether it satisfies the constraints. The HS system applies its constraints after each problem solving step, and it learns before it has completed a correct solution. Second, the FAILSAFE system relies on the fact that the length of a floor plan solution is known *a priori* to identify failures. In contrast, the state constraint representation provides HS with a general method for identifying failures. Third, the FAILSAFE system learns one new rule for each failure, while HS learns two new rules in response to each constraint violation. The cause of this difference deserves to be analyzed in more detail than we can do here. Fourth, like other EBL systems, FAILSAFE uses its domain theory to construct explanations, a potentially complicated process which might reauire search, and which might fail if the domain theory is incorrect or incomplete. HS replaces the construction of explanations with pattern matching. Fifth, the FAILSAFE system can assign blame to rules which are several steps removed from the point of failure detection. This is an advance upon the HS system, in which blame is always assigned to the last rule to fire before failure detection.

Psychological models of learning do not usually address the problem of the cognitive function of general knowledge in procedure acquisition. One exception is the ACT* theory proposed by Anderson (1989), which claims that declarative knowledge structures are *proceduralized* during problem solving. The main difference between proceduralization and constraint violation is that in proceduralization declarative knowledge only participates in the creation of *initial* rules; further improvement of those rules is handled by empirical learning mechanisms such as composition and strengthening. In constraint violation declarative knowledge continues to influence rule revisions during the entire life time of the rule. The planning net model of counting competence proposed by Smith, Greeno, and Vitolo (in press) addresses the same phenomenon as the HS system--children's flexibility in moving between different counting tasks--and their model also assumes that the source of this flexibility is a declarative encoding of the counting principles. However, Smith, Geeno, and Vitolo (in press) characterize their model as a competence model rather than as a process model, disclaiming any psychological reality for the processes they describe. It is therefore unclear how to conduct a comparison between their system and ours.

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